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Article

How Offshoring Can Affect the Industries' Skill Composition

Daniel Horgos [1,*] and Lucia Tajoli [2]

[1] Department of Economics, Helmut Schmidt University, University FAF Hamburg, Holstenhofweg 85, 22043 Hamburg, Germany
[2] Dipartimento di Ingegneria Gestionale, Politecnico di Milano, via Lambruschini 4/b, 20156 Milano, Italy; E-Mail: lucia.tajoli@polimi.it

* Author to whom correspondence should be addressed; E-Mail: horgos@hsu-hh.de; Tel.: +49-40-6541-2022; Fax: +49-40-6541-2042.

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Abstract: While most of the offshoring literature focuses on the effects on relative wages, other implications do not receive the necessary attention. This paper investigates the effects on the industries' skill ratio. It summarizes the empirical literature, discusses theoretical findings, and provides empirical evidence for Germany. As results show, effects are mainly driven by the industry where offshoring takes place. If offshoring takes place in high-skill intensive industries, the high-skill labor ratio increases (vice versa if offshoring takes place in low-skill intensive industries). Results are in line with other empirical findings, however, they seem to contradict theoretical causalities. Thus, we additionally discuss possible explanations.

Keywords: offshoring; labor market implications; skill ratio; skill composition

JEL classifications: F16; J21

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1. Introduction

During the last decades, implications of offshoring became an important issue in economic research and political discussion as well. The process of slicing up the value chain, relocating parts of the production process abroad and importing the respective intermediate goods instead is assumed to significantly affect domestic labor markets.[1] Most theoretical and empirical contributions focus especially on the implications of offshoring on relative wages.

Feenstra and Hanson (1996, 1999) [1–3] e.g., assume a relatively high-skill abundant economy that relocates its relatively low-skill intensive part of production abroad. Their theoretical results are backed by empirical findings for the US-Mexican case and show that offshoring induces a decrease in the demand for relative low-skilled labor. This leads to an increase in relative wages of the high-skilled. Since the relocated production fragment is assumed to be relative low-skill intensive for the offshoring economy, but relative high-skill intensive for the inshoring economy, relative wages of the low-skilled decrease in both of them. Since the leverage distinguishes between different factor owners, this result is known as the "factor bias" of offshoring [1–3]. Whereas Feenstra and Hanson assume only one industry, Arndt (1997, 1998) [4–6] distinguishes between a relative low and a relative high-skill intensive industry and, thus, moved the focus towards more disaggregated levels [4–6]. Results show that the effects of offshoring on relative wages depend crucially on the skill intensity of the industry where offshoring takes place. If the relative low-skill intensive industry relocates parts of the production process abroad, relative low-skill wages increase, whereas relative high-skill wages increase if offshoring takes place in the relative high-skill intensive industry. These results are known as the "sector bias" of offshoring.

While it would be exhausting to discuss which of the two effects prevails, both of them provide interesting insights on how offshoring can affect the domestic labor market. While the factor bias illuminates substitutional forces between domestic and foreign factor owners, the sector bias points to a productivity enhancing dimension. Similar to the process of technological change, the effects of the sector bias are initiated by a reduction of unit costs that is resulting when offshoring takes place. The reduced unit costs enable a wage markup. Depending on the skill-intensity of the production structure of the industry where offshoring takes place, the wage markup favours either relative low or high-skilled labor.

Most of the economic literature that investigates labor-market effects of offshoring keeps the focus on the effects on relative wages (see e.g., Berman *et al.*, 1994; Egger and Egger, 2002; Egger and Falkinger, 2003; Geishecker and Görg, 2005; Hijzen *et al.*, 2005; Hijzen, 2007; Horgos, 2011a; Kohler, 2009; and Foster-McGregor *et al.*, 2013 [7–15]). It is important to note that offshoring, as shown by Blinder (2009), is not only putting low-skilled labor under pressure [16]. According to the relative "offshorability" of tasks, high-skilled labor may be affected in the same way (see e.g., Blinder, 2009, Oldenski, 2012 or Michaels *et al.* (2013) [16–18]).[2]

The effects on relative wages, however, are by no means the whole story. In general equilibrium-and even within the labor market-there exist several other important and interesting implications. Some

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[1] In this contribution, offshoring is used as in most recent publications, without distinguishing between the imports of intermediates produced in foreign affiliates (FDI) and the imports of intermediates produced at arms' length (international outsourcing).

[2] As Michaels *et al.* (2013) illuminate, empirical analyses face the problem of disentangling the effects of offshoring from pure technological progress. The presence of offshoring effects that are analogous to those of technological change in terms of productivity are especially relevant in the most recent wave of the offshoring literature, adopting the assumption that not labor but tasks are relocated abroad (see Grossman and Rossi-Hansberg (2008) and subsequent literature [19]).

of them have been recently addressed in the work by Baldwin and Robert-Nicoud (2014), following the trade-in-tasks approach [20]. One of these issues is the effect of offshoring on the industries' skill composition: How does the industries' production structure (the high to low-skill labor ratio) change when offshoring activities take place? As in the newer models offshoring arises endogenously, depending on relative offshoring costs, the range of offshored tasks varies intensively across sectors. Offshoring induces different, industry-specific effects on the demand of skills. In this respect, however, only few contributions emerged recently providing a far less clear picture compared to that provided for the effects of offshoring on relative wages. One reason for the possible ambiguities is the existence of diverse forces that get visible when investigating the effects of offshoring activities on the skill composition. On the one hand, there exists a direct "offshoring-effect". Consider e.g., that the low-skill intensive industry relocates its high-skill intensive production fragment. A very direct effect is that relative demand of high-skilled labor decreases. This effect, however, gets accompanied by a more indirect "wage-effect". In the mentioned scenario, offshoring in the low-skill intensive industry induces a reduction on unit costs and, thus, a wage markup paid for low-skilled labor. As low-skilled labor gets more expensive, the industry substitutes low with high-skilled labor what increases relative demand of the high-skilled. While the direct offshoring-effect depends on the skill intensity of the relocated production fragment, the industry where offshoring takes place is important for the wage-effect. Since these effects are only rarely examined by economic literature so far, there is a need for further investigations. The specific contribution of this paper is to examine the effects of offshoring on the industries' skill composition, distinguishing between offshoring in high and low-skill intensive industries and between offshoring of high and low-skill intensive production parts as well.

Therefore, Section 2 provides an empirical literature review of existing contributions investigating the effects of offshoring on the industries' skill composition. Section 3 discusses the theoretical background. Section 4 conducts the empirical analysis using data for the German economy. As results show, effects are insignificant on more aggregated industry levels. When examining more disaggregated industry levels, significant results occur showing that the implications differ strongly between the different industries where offshoring takes place. Contrary to the theoretical models (but in line with other empirical findings), the high-skilled labor ratio increases if offshoring takes place in relatively high-skill intensive industries and decreases if the relative low-skill intensive industries relocate production parts. Since there seems to be a puzzle between the theoretical predictions and empirical findings, Section 5 discusses the results in greater detail in order to provide suggestions on how to reconcile theory with empirics. Section 6 concludes by summarizing the major results.

2. Offshoring and the Industries' Skill Composition: A Look at some Empirical Results

Most empirical contributions focus on the implications of offshoring on relative wages, whereas the literature on how offshoring affects the industries' skill composition is relatively rare. Furthermore, the few empirical contributions existing do not distinguish between the different industries where offshoring takes place and the different production fragments that are offshored. Cross-industry regressions make the implicit assumption that the estimated cost or production function is the same across industries. However, even if a similar production function across manufacturing industries can be assumed, very different factor intensities may be used across those industries. This heterogeneity in factor intensities is relevant for offshoring choices, as highlighted by Grossman and Rossi-Hansberg (2008) [19]. Regressions that do not consider these industry peculiarities are not able to depict the divers effects of offshoring.

Studies that differentiate between imports of intermediate inputs from different countries of origin consider the mentioned industry peculiarities partly. It may be assumed that imports from less developed and emerging economies with low (unskilled) labor costs are intensive in unskilled labor. Examples of these studies are given by Egger and Egger (2005) and Geishecker (2006), who consider imports of intermediate inputs in Western European countries from Central and Eastern Europe and find that these imports have a positive and significant effect on relative employment or the relative wage of skilled workers [21,22]. However, as we meanwhile know from the discussion around Blinder (2009), imports from countries with relatively low labor costs do not necessarily need to be relatively unskilled-labor intensive [16]. Especially in the CEECs, the endowment of skilled workers is abundant relative to other areas of the world. Therefore, controlling for the geographical origin of the intermediate inputs is only a partial attempt to take the factor intensity of these inputs into account.[3]

A couple of studies explicitly address the issue of differences across manufacturing industries that can affect the impact of offshoring. The first is the work by Geishecker and Görg (2005), who assess the effect of international fragmentation of production on wage levels in Germany [10]. Results show that the extent and the dynamic of fragmentation of production differ between industries. They don't find a significant effect of international fragmentation when including all industries into the regression. However, when splitting the sample and distinguishing between skill-intensive industries and low-skill intensive ones, a very differentiated effect of offshoring occurs. Their results highlight a positive and significant effect of offshoring on the wages of high-skilled workers in the skill-intensive industries and a negative and significant effect on the wages of low-skilled workers in the low-skill intensive industries. This sharp difference in results highlights the importance of assessing carefully the effect of offshoring in each specific context. However, their analysis is restricted to the effects on relative wages only.

Geishecker (2006) examines the effects of offshoring on cost shares in variable costs of high- and low-skilled labor. These cost shares can be interpreted as a composite expression of relative labor demand that reflects both, relative employment and relative factor prices. One crucial value added by Geishecker (2006) to the literature is the distinction of intermediate inputs from different source countries. His results show that offshoring to Central and Eastern European Countries implies a significant negative pressure on manual workers' wages in Germany [22]. While Geishecker (2006) focus on cost shares, Hijzen *et al.* (2005) investigate cost as well as employment shares for the UK. Their results show that offshoring decreases employment of low, medium and high-skilled labor in the UK between 1982 and 1996. The effect is most significant for the low-skilled [11].

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[3] A recent work by Becker *et al.* (2009) addresses the issue of which types of tasks are kept at home by German multinationals when offshoring occurs. Data limitations, however, do not allow to model explicitly which types of tasks are offshored [23]. For this sample of MNEs, the location where offshoring takes place does not seem to matter for the effect on domestic employment.

While both contributions consider the industries' skill composition only indirectly, Falzoni and Tajoli (2012) investigate the effects of offshoring on high to low-skilled employment for the Italian economy [24]. In spite of differences in the overall manufacturing specialization between Italy and Germany, offshoring is in both economies more extensive in relative skill-intensive industries. Even when considering employment rather than wages, the results by Falzoni and Tajoli (2012) are consistent with the ones by Geishecker and Görg (2005), as the impact of offshoring appears to be only weakly significant and not robust when running the regressions across all manufacturing industries [10,24]. However, when splitting the sample between skill-intensive and unskill-intensive industries, the picture changes, as the impact on the skill composition differs across industries. Offshoring has a significant negative effect on relative employment of skilled workers in the unskilled-intensive sectors, while it has a significant positive effect on relative employment of skilled workers in the skill-intensive industries. Consequently, the context in which offshoring takes place is crucial for the implications.

Our contribution differs from the above mentioned studies in several aspects. First, we investigate the effects of offshoring on the industries' skill composition in the German economy. In order to consider industry peculiarities properly, we also move the analysis to more disaggregated industry levels. Second, we also distinguish between the skill intensity of the production fragment that is offshored additionally to the industry where offshoring takes place. This very detailed examination of the offshoring process provides the possibility to interpret the results in terms of the factor and the sector bias of offshoring. Before entering the econometric analysis, the next section will briefly discuss the factor and the sector bias of offshoring from a theoretical perspective.

3. Short Sketch of the Theoretical Background

As in the empirical literature, contributions investigating the effects of offshoring on the industries' skill composition theoretically are relatively rare. Even if the broadly known framework of Feenstra and Hanson (1996, 1999) [1–3] does not explicitly investigate the implications on the skill ratio, some results can be drawn from this model [1–3]. Assuming a high-skill abundant economy (without distinguishing between different industries) where offshoring takes place by relocating low-skill intensive production parts abroad, demand of low-skilled labor decreases. Straight forward, relative wages of high-skilled labor increases in both, the offshoring as well as the inshoring economy. With respect to the offshoring economy, the relocated production block is assumed to be relatively low-skill intensive whereas, regarding the inshoring economy, the relocated production block is assumed to be relative high-skill intensive instead. The follow-up effects on the skill ratio are twofold: In the high-skill abundant northern economy the skill ratio should on the one hand increase as it is the relative low-skill intensive production part that gets relocated. On the other hand, due to the increasing effect on relative wages of the high-skilled, there should be a substitution effect towards more low-skill intensive production. In the aggregate (what is the focus of the Feenstra and Hanson model), the effects of offshoring on the skill ratio can be assumed to be ambiguous. Proposition 1 summarizes this pattern.

Proposition 1: *Concerning the aggregated whole economy, the high-skilled labor ratio is assumed to increase if low-skill intensive production fragments are relocated abroad. However, since the decrease in low-skilled labor demand increases relative high-skilled wages, there should also be a substitution effect towards more low-skilled labor. Summing up, the implication of offshoring on the skill ratio of production is assumed to be ambiguous in the aggregate.*

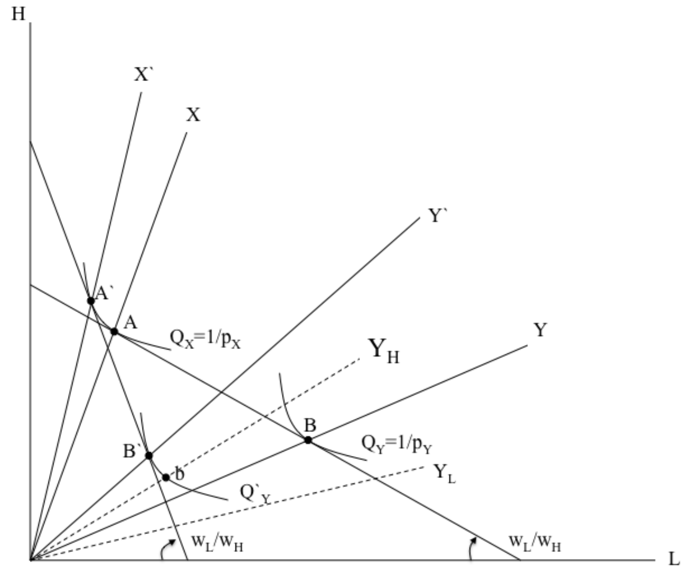

Figure 1. Labor Market Effects of Offshoring–The Sector Bias.

One theoretical model that explicitly focus on the effects on the industries' skill ratio is the framework of Arndt (1997, 1998) [4–6] [4] Assuming two industries with two kinds of labor, the model focus on more disaggregated industry levels and investigates offshoring within a traditional Heckscher-Ohlin framework. The essence of the results is that the effects on relative wages do not depend on the skill intensity of the relocated production block. By contrast, the skill intensity of the industry where offshoring takes place is the driving parameter: Due to the small country assumption, offshoring enables an additional wage premium since the industries' unit costs decrease. Depending on the relative skill intensity of the respective industry, this wage premium favors either high or the low-skilled workers. In this form, offshoring induces a similar skill bias already known from technological progress. Thus,

[4] This model got extended in several contribution in order to investigate different aspects of offshoring effects. Deardorff (2001) [25,26] e.g., illuminates the importance of the relative factor intensity of the relocated production blocks [25,26]. Egger and Falkinger (2003) consider different modes of final goods production and examine several different equilibrium situations in order to determine the dominance of the factor or the sector bias of international offshoring [9]. Kohler (2009) investigates differences between the sector bias models and the literature that emerged on task trade, initiated by Grossman and Rossi-Hansberg (2008) [14,19]. In his contribution, Kohler specifically mentions the importance of offshoring heterogeneous tasks at the industry level and thus, the sector bias of offshoring and how this sector bias model of offshoring can be reconciled with the task trade framework of Grossman and Rossi-Hansberg. Another important extension of the most recent approach is to include terms-of-trade effects into the model, dropping the small country hypothesis. In this contribution, we maintain the small country assumption in order to keep international prices constant and focus on the other types of effects, although when not realistic for the German case.

relative high-skill wages increase if offshoring takes place in the relative high-skill intensive industry and vice versa for the relative low-skill intensive one. The effects are summarized in Figure 1.

As can be seen in this Pearce-Lerner diagram (with high-skilled labor (H) on the vertical and low-skilled labor (L) on the horizontal axis), there exist two industries, the relative high-skill intensive industry (X) and the relative low-skill intensive one (Y). The factor intensities are given by the two expansion paths X and Y. At the initial equilibrium, production takes place at points A and B, where the unit value isoquants Q interact with the relative price line w_L/w_H. The Y industry produces at point B with the use of two intermediate products Y_H (relative high-skill intensive) and Y_L (relative low-skill intensive).

Now suppose that, e.g., due to advances in technology and communication, offshoring gets possible and that the low-skill intensive industry (e.g., the import competing one in a high-skill abundant economy) relocates production of its relative low-skill intensive intermediate abroad and imports the respective input instead. Thus, domestic production of Y consists solely of production of the relative high-skill intensive component Y_H. At the initial relative wage ratio, factor intensity in the Y industry shifts to the more high-skill intensive expansion path Y_H (let's call this the "offshoring-effect"). While the relative price of Y remained unchanged, overall costs decrease due to the lower-cost procurement from the foreign country, shifting the unit isoquant inward to Q'_Y. Due to this decrease in costs, the unchanged relative price of Y is now inconsistent with the initial relative wage ratio. Therefore, Y producers increase the relative demand for low-skilled labor (since it is the relative low-skill intensive industry). Relative wages of the low-skilled increase as long as the new ratio is tangent to the new isoquant Q'_Y, resulting in the new equilibrium of production at A' and B'. A substitution process towards more high-skill intensive production follows consequently (let's call this the "wage-effect"). As can be seen with the new expansion paths X' and Y', both effects (the "offshoring-effect" and the "wage-effect") induce skill shifts in both industries towards more high-skill intensive production patterns (regarding the assumed scenario that the low-skill intensive industry relocates it's low-skill intensive production block). The framework can now easily be extended to generalize the results, that are summarized in Proposition 2.

Proposition 2: *The implications of offshoring on the industries' skill ratio are driven by a direct "offshoring-effect" as well as an indirect "wage-effect". If offshoring takes place in the relative low-skill intensive industry, the industries unambiguously shift production towards more high-skilled labor when relocating the relative low-skill intensive production block. If the industry relocates its high-skill intensive fragment, results are ambiguous since the wage and the offshoring-effect work in different directions. If offshoring takes place in the relative high-skill intensive industry, the industries' unambiguously shift production towards more low-skill intensive processes when relocating the relative high-skill intensive fragment. Again, results are ambiguous if the industry offshores its low-skill intensive production process.*

Theoretical results on the implications of offshoring on the industries' skill composition are not as clear cut as the implications on relative wages. Results depend on the level of industry aggregation as well as on more specific characteristics of the offshoring process: on which industry relocates parts of it‘s production fragments, on the relative skill intensity of the relocated parts, and, from a more theoretical point of view, also on the model set-up and its assumptions (as e.g., the elasticity of substitution between low and high-skilled labor) predicting if the wage-effect outperforms the offshoring-effect or vice versa.[5]

4. Empirical Evidence for Germany

This section empirically investigates the effects of offshoring on the within industries' skill ratio for Germany from 1991–2000. Before describing the data and presenting the estimation results, we distill three testable hypothesis from the theoretical examination above:

(i) On more aggregated industry levels (as e.g., the whole economy or the manufacturing sector as a whole), different forces are expected to occur that sum up to insignificant effects of offshoring on the industries skill ratio.

(ii) When conducting the analysis on more disaggregated industry levels, effects should get significant and, due to industry heterogeneity, illuminate different patterns if offshoring takes place in different industries.

(iii) Following the framework of the sector bias of offshoring, increasing high-skill ratios would be expected if offshoring takes place in relative low-skill intensive industries and vice versa for relative high-skill intensive ones.

Data

The empirical analysis is based on data for the German economy from 1991–2000. To measure offshoring activities on the two-digit NACE industry level, we use input-output tables provided by the German Federal Statistical Office. Since offshoring can not be directly observed at the industry level, there is the need for adequate proxies. Therefore, literature developed several indices with some of them quite common in use.[6] In this paper we use a frequently used index called Vertical Specialization (VS). The VS-index is introduced in Campa and Goldberg (1997) and applied e.g., in Feenstra (1998), Strauss-Kahn (2003) or Horgos (2209). It can be calculated using

$$VS_t = \sum_{j=1}^{n} \sum_{w=1}^{z} \frac{f_{wt} \cdot q_{wjt}}{p_{jt}} = \sum_{j=1}^{n} \sum_{w=1}^{z} \frac{(m_{wt}/s_{wt}) \cdot q_{wjt}}{p_{jt}} \quad (1)$$

[5] In the above assumed scenario (when the relative low-skill intensive industry relocates its relative low-skill intensive part of production), the wage and the offshoring-effect work in the same direction: Shifting production towards more high-skill intensive activities. However, using this graphical framework, it is easy to show, that results would not be as clear cut when offshoring would take place in the relative low (high)-skill intensive industry by relocating its relative high (low)-skill intensive part of production. As Horgos (2011b) shows formally, results strongly depend on the assumed elasticity of substitution between low and high-skilled labor [27]. Assuming Cobb-Douglas elasticities, the wage-effect always outperforms the offshoring-effect, yielding unambiguous results.

[6] There is no general consensus on which is the most appropriate offshoring measure. Different variants of indices capture different aspects of the offshoring phenomenon. For a comparative analysis of different offshoring indices, their design, quality, and econometrical behavior when investigating labor market effects see Horgos (2009) [28]. Castellani *et al.* (2013) investigate offshoring indices for several European economies between 1995 and 2006 [29].

with q_{wjt} as industry j's total inputs of good w (domestic as well as from abroad) in year t, p as the level of production and f as a ratio estimating the international fraction of the inputs [28,30–32]. The international estimation ratio f relates imported goods m to domestically used goods s. The goodness of the VS-index depends strongly on the international estimation ratio f. Equation (1) presents the aggregated version of the index. The index is calculated at the level of the industry when applying the regressions for the more disaggregated industry levels below.[7]

Information of the input-output tables is also used to obtain the industries' output (Q_{jt}). We enrich the input-output table data with information from the German Socio Economic Panel (GSOEP) provided in yearly waves since 1984 by the DIW Berlin.[8] The GSOEP observes gross wages from around 40,000 individuals, including additional payments like e.g., 13th or 14th month pay or Christmas bonuses. Individuals in the GSOEP are additionally classified with respect to the International Standard Classification of Education, provided by UNESCO (1997) [34]. Using information on the level of education, we calculate the industries' mean wages of high-skilled labor (w_{jH}) as well as their low-skill intensive counterparts (w_{jL}).[9] In order to obtain information on the industries skill composition, we also refer to the German SOEP and calculate the fraction of high to low-skilled labor per industry j (H_j/L_j).[10] Overall, our panel data for the German economy covers the years 1991–2000 and consists of the two-digit NACE industries' skill composition, their offshoring intensity, output, as well as relative high-skill wages.

Table 1 summarizes descriptive statistics in order to get a first idea of the variables in the sample. For a more detailed descriptive overview of the variation of the main variables see Figure 2.

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7 As shown in Horgos (2009), the VS-index has quite good properties proxying offshoring activities, especially on more disaggregated industry levels [28]. Another index used frequently is imported inputs over total intermediate purchases (see e.g., Feenstra and Hanson, 1996 [2]). The main difference of the VS-index is that it uses total production instead of total intermediate inputs as reference in the denominator. Some contributions also distinguish between a narrow and wide version of the offshoring index or between service or material offshoring. The VS-index applied here corresponds to the wide version and focuses on material offshoring.

8 For detailed information on the German Socio Economic Panel see Haisken-Denew and Frick (2005) [33].

9 According to the ISCED, low-skilled workers are defined as workers with primary (1), lower secondary or second stage of basic education (2), whereas high-skilled individuals are assumed to have some form of post secondary education (4, 5, or 6).

10 As Falzoni and Tajoli (2012) mention, measuring the skill level through educational attainments is closely related to the supply side of the labor market and highly correlated to other frequently used measures, as e.g., the white/blue collars ratio [24]. In this contribution, we calculated the H_j/L_j-ratio using the ï£¡International Standard Classification of Educationï£¡ (ISCED) from UNESCO (1997). The ISCED provides a standardized scheme classifying individuals in (1) primary education; (2) lower secondary education or second stage of basic education; (3) secondary education; (4) postsecondary, nontertiary education; (5) first stage of tertiary education, or (6) second stage of tertiary education. In order to construct the H_j/L_j-index; (1) and (2) are considered as individuals with lower education whereas higher-educated individuals are those of group (5) and (6). Still, educational levels of the workforce can be a poor proxy of the actual level of skills employed in production, for at least two reasons: formal education levels do not capture the overall skills that workers have accumulated over time, and labor market imperfections might place highly educated people to perform tasks requiring low skills.

Table 1. Descriptive Statistics of the Variables in the Sample.

	N	Mean	Sd	Min	Max
H/L	273	1.41	1.54	.14	15
ω	241	1.60	.63	.28	4.80
Q	300	48735.86	48445.69	783	251568
VS	296	.11	.05	0	.28

H/L denotes the industries' high-skill labor ratio, ω the relative wage of the high-skilled per industry, Q the industries' output and VS the vertical specialization index of offshoring activity.

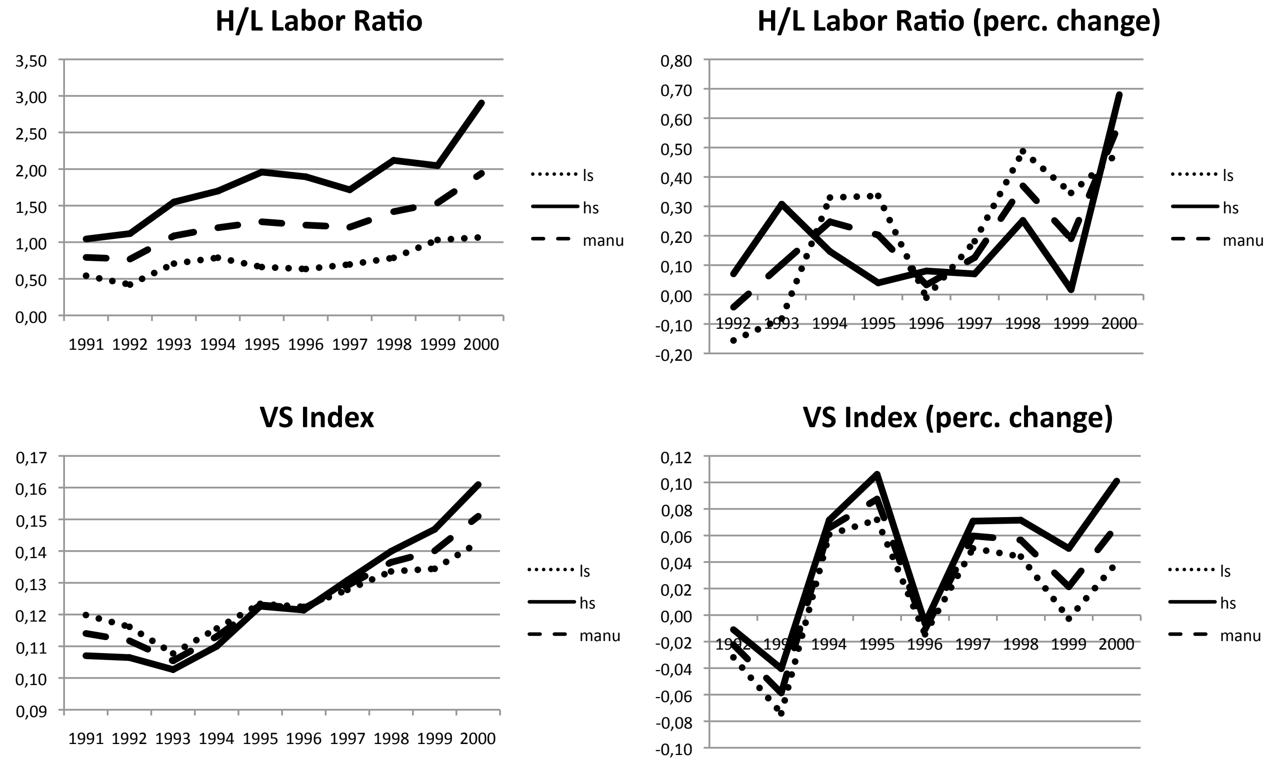

Figure 2. Descriptive Statistics: High-Skill Labor Ratio and Offshoring Activity.

As expected for developed economies, the figure shows a skill upgrading effect in the German manufacturing industry. The growth rate of the H/L ratio, however, is fluctuating over the years. In addition, offshoring activities (the VS-index) increase over the considered time period. While fluctuating in the first years from 1991–1995, a strong increase occurred after 1995. When examining the development of the VS-index in greater detail, we observe that in Germany offshoring is more pronounced in the relative high-skill intensive industries than in the relative low-skill intensive ones.[11] As shown in Falzoni and Tajoli (2012), this pattern is similar than the offshoring activities in Italy [24].

In order to investigate the empirical importance of which industry offshores which parts of production (what is of special interest in this contribution), the magnitude and development of the VS-index are also calculated on more disaggregated industry levels. For the calculation of the disaggregated offshoring index, we distinguish between which industry j imports which kind of intermediate w. Since the input-output data used in this contribution differentiates between inputs that are domestically purchased and imported inputs, we are able to calculate the numbers directly without applying the proportionality assumption, what is necessary when data on imported inputs are not available at the level of the industry (see Winkler and Milberg, 2009 for a discussion [35]). The numbers are presented in Table 2.

Table 2. Level and Development of Offshoring in Germany.

	Low-Skill Int. Industries		**High-Skill Int. Industries**	
	Low-Skill Parts	**High-Skill Parts**	**Low-Skill Parts**	**High-Skill Parts**
1991	6.01%	3.02%	2.10%	7.78%
1995	5.82%	3.21%	1.86%	9.09%
2000	6.46%	4.19%	2.10%	12.39%
Δ 1991 − 2000	7.49%	38.74%	0.00%	59.25%

Numbers in the table are calculated using the VS-index presented in Equation (1). For offshoring low-skill intensive production parts of the relative low-skill intensive industries (Column 1), we consider only the import of low-skill intensive inputs w in relative low-skill intensive industries j. As the table shows, in relative low-skill intensive industries, the average level of offshoring high-skill intensive production parts (Column 2) is 3.02 percent of the production value in 1991. The offshoring index for low-skill intensive parts of production in this industry reaches 6.01 percent in 1991. These numbers show that the average offshoring intensity of low-skill intensive parts in relative low-skill intensive industries is nearly double as high as the offshoring intensity of high-skill intensive parts in those industries. In 2000, the offshoring index for high-skill intensive parts (4.19 percent) reaches two third of the offshoring index for low-skill intensive parts (6.46 percent). Considering the offshoring dynamic in the 1990s (Line 4), there is a much stronger increase in relocating high-skill intensive production parts (increase of 38.74 percent) compared to relocating low-skill intensive parts (increase of 7.49 percent). In relative high-skill intensive industries, by contrast, the average level of offshoring high-skill intensive production parts is much higher then its low-skill intensive counterparts. In 1995, e.g., the offshoring index in relative high-skill intensive industries is on average 9.09 percent for high-skill intensive production fragments (Column 4), whereas the offshoring index reaches on average only 1.86 percent when

[11] In order to distinguish between relative low and relative high-skill intensive industries of the German manufacturing sector, we follow the results of a cluster analysis done by Geishecker and Görg (2005) [10]. Another possible classification method would be the definition of the skill intensity of sectors according to their R&D activities. A list of which industry belongs to which skill classification as well as a discussion on the classification scheme is presented in Table A1 in Appendix A.

considering the relocation of low-skill intensive production fragments (Column 3). Despite the relative high levels of the index, the increase of offshoring high-skill intensive production parts is much more pronounced as well. During the 1990s, the offshoring index of high-skill intensive production parts in the relative high-skill intensive industries increased by 59.25 percent, whereas offshoring low-skill intensive parts stayed stable. These descriptive findings may be seen as support for the argument of Blinder (2009) that high-skill intensive tasks are relocated intensively, also in high-wage economies as e.g., Germany [16].

Empirical Methodology and Results

In order to assess the implications of offshoring on the industries skill ratio, we estimate

$$(H/L)_{jt} = \beta_0 + \beta_1 \omega_{jt}(l) + \beta_2 Q_{jt}(l) + \beta_3 VS_{jt}(l) + \epsilon_{jt} \qquad (2)$$

for different levels of industry aggregation. The high-skill labor ratio H/L of industry j is regressed on a constant, relative high-skill wages $\omega_{jt} \equiv \frac{w_{Hjt}}{w_{Ljt}}$, the industry's output Q, offshoring measured with the VS-index, and dummies for the years t capturing the time trend. ϵ is a typical error term. The estimation strategy is similar to the majority of other empirical analyses on the implications of offshoring, however, with some differences that are worth being mentioned: Most contributions investigate the effects of offshoring on relative wages. For those estimations, it is necessary to include at least industry output, offshoring and a variable capturing technological progress as exogenous variables. In order to control for technological progress, some authors include the industries' R&D intensity. If this information is not available, as it is in the majority of cases, the authors help out in including variables that control for the industries' factor composition. This, however, is the endogenous variable in our approach. We discuss this peculiarity in the robustness checks presented below.

When including contemporaneous observations for the endogenous as well as exogenous variables, an endogeneity problem may arise (not only with respect to relative wages). We therefor ran Durbin-Wu-Hausman tests to proof if possible endogeneity could significantly bias the results. In order to avoid the resulting bias and to secure pure exogenous variables on the right hand side, we decided to perform an instrumental variable regression and instrument all the exogenous variables with its one-period lagged components (l).

To estimate Equation (2) for the different levels of industry aggregation we use the random-effects estimator (RE) since we do not assume that the exogenous variables are strategically correlated at the industry level. The Breusch and Pagan test for unobserved heterogeneity as well as the Hausman test statistically confirm the use of a random effects model. Additional tests for consistency of the estimated error matrix, the modified Wald test for groupwise heteroscedasticity as well as the Wooldridge test for autocorrelation show that the traditional error terms are indeed driven by a heteroscedastic error structure as well as autocorrelation.[12] Thus, we use the robust Huber / White sandwich estimator for all regressions. With this procedure, also taking possible outliers into account, we are able to assure the consistency and the comparability of the estimation results. The results are presented in Table 3.

[12] Table A2 in Appendix B report the test statistics.

Table 3. Effects on the Industries' High-Skill Labor Ratio.

	Whole Economy	Manufacturing Sector	Disaggregated Industry Levels	
ω	-0.0185 (-0.39)	-0.0313 (-0.76)	-0.0449 (-0.83)	-0.0209 (-0.65)
Q	$2.79e$-07 (0.12)	$8.88e$-07 (0.31)	$-3.79e$-06 (-1.10)	$-3.41e$-06 (-1.31)
VS	1.5100 (0.51)	2.2014 (0.81)	-	-
i VS (Y)	-	-	-1.1057 (-0.57)	-
i VS (X)	-	-	9.9336 ** (2.13)	-
i VS (Y $\rightarrow$ L)	-	-	-	-3.8644 * (-1.92)
i VS (Y $\rightarrow$ H)	-	-	-	-10.8943 *** (-2.88)
i VS (X $\rightarrow$ L)	-	-	-	30.6530 (1.56)
i VS (X $\rightarrow$ H)	-	-	-	8.2695 ** (2.11)
cons.	1.6750 *** (5.57)	1.5259 *** (3.43)	1.6165 *** (4.85)	1.9531 *** (6.53)
Year Dummies	YES	YES	YES	YES
Obs.	190	165	165	330
Groups	25	20	20	40
Prob $>$ chi2	0.0000	0.0000	0.0000	0.0000

Endogenous variable: within industries' high-skill labor ratio (H/L); (z-Statistics in parantheses); */ **/*** indicates significance at 10/5/1 percent.

As the results show for the more aggregated levels of the whole economy and the manufacturing sector (Columns 1 and 2),[13] effects are overall quite insignificant. As we figured out in the theoretical section and summarized in Hypothesis (i), different forces appear that are expected to level out to insignificant effect in the aggregate. Our empirical set-up is not able to capture the different effects, results however confirm Hypothesis (i). Regarding the offshoring index VS, implications on the industries' high-skill labor ratio are not at usually reported levels of statistical significance. The increasing tendency on the high-skilled labor ratio in the aggregate is not statistically significant, neither when regarding the whole economy, nor with respect to the manufacturing sector as a whole.

[13] Since the examination here focus on material offshoring, we exclude the service sector in all regressions.

Interesting results occur when moving the analysis towards more disaggregated levels of industry aggregation (Column 3 and 4). First, consider Column 3. We replace the aggregated VS-index by two variables interacting the VS-index with dummy variables set one for either the relative low or the relative high-skill intensive industries (both as subsamples of the manufacturing sector). Therefore, i VS (Y) proxies offshoring taking place in the relative low-skill intensive Y industry and i VS (X) offshoring in the relative high-skill intensive X industry. The results support hypothesis (ii): The implications of offshoring on the industries skill ratio strongly depend on the industries where offshoring takes place. If it takes place in relative low-skill intensive industries (Y), the high-skill labor ratio shows a decreasing tendency, however, the effect is not statistically significant. By contrast, if offshoring takes place in the relative high-skill intensive industries (X) the industries' high-skill labor ratio increases, statistically significant at the level of 5 percent. This result goes in hand with the pattern shown in other empirical investigations (see e.g., Falzoni and Tajoli (2012) for results on the Italian economy), however, contradicts with the pattern expected from the theoretical literature [24]. As we discussed above and summarized in hypothesis (iii) the high-skill labor ratio should increases if offshoring takes place in the relative low-skill intensive industries and decrease in the relative high-skill intensive ones. The empirical results here support exactly the opposite (what will be discussed in detail in the next section).

In order to move to a higher level of disaggregation, Column 4 extends the analysis by further distinguishing the offshoring activities of the two industry samples. i VS (Y $\rightarrow$ L) proxies offshoring of the low-skill intensive production parts (L) in the low-skill intensive industry (Y), whereas i VS (Y $\rightarrow$ H) proxies offshoring activities of the high-skill intensive fragments. For the high-skill intensive X industries we continue this notation and get i VS (X $\rightarrow$ L) as well as i VS (X $\rightarrow$ H). Again, we achieve a significant increasing effect in the high-skill intensive industries and a significant decreasing effect in the low-skill intensive ones. The interesting point to mention is that the implications of offshoring on the industries skill ratio seem to be primarily driven by the industry where offshoring takes place, and only to a minor extent by the skill intensity of the relocated production fragments.[14]

Consider e.g., the low-skill intensive Y industry: if the industry offshores its high-skill intensive production parts (i VS Y $\rightarrow$ H), the estimated coefficient on the industries' high-skill labor ratio is negative, quite high, and at a high level of statistical significance. If the industry offshores its low-skill intensive parts of production (i VS Y $\rightarrow$ L), the estimated coefficient is slightly smaller, but still highly significant negative. Thus, even if the industry offshores its low-skill intensive parts of production, production shifts towards more low-skilled labor. The same pattern holds for the high-skill intensive X industry. If the industry offshores its high-skill intensive parts (i VS X $\rightarrow$ H), the effect on the industries' high-skill labor ratio is strongly significant positive. The effects also show a positive tendency

[14] An additional interpretation of these industry-specific results of offshoring rests on the likely upgrade of firms' organizational and technological structure after offshoring. If technological/organizational change occurs after offshoring (or if offshoring is driven by such kind of management strategies), and this re-organization concentrates activities in core functions, the skill ratio would be significantly more polarized regardless of the specific intensity of the offshored fragment of production. See e.g., Davis and Naghavi (2011) or Bartel, Lach and Sicherman (2008) for further discussion on this issue [36,37]. The authors thank one of the referees for pointing this out.

(even when being slightly outside the common level of reported statistical significance) if the industries relocate their low-skill intensive parts of production (i VS X $\rightarrow$ L).[15]

Robustness Checks

Beyond the typical statistical caveats that we already discussed while presenting the regression methodology above, an additional problem arises when assuming that the lagged dependent variable may be part of the data-generating process. In order to provide robust estimates in such cases, we need to included the lagged endogenous variable as an additional regressor. The RE models applied above are not able to eliminate a possible dynamic panel bias (see Nickell, 1981; Bond, 2002; or Roodman, 2006 for a summary [38–40]). In order to check if our results are robust even when adding the lagged dependent variable to the regressors, we applied the Anderson and Hsiao (1982) level estimator and system GMM regressions as robustness check [41]. Results of these robustness checks are presented in Table 4.[16]

Results of the robustness check confirm the findings of the RE regressions presented above. Both estimation versions, the 2SLS estimation (robustness check 1) as well as the system GMM estimation (robustness check 2) exhibit insignificant effects of offshoring on the high-skill labor ratio if we consider more aggregated industry levels like the whole economy (Column 1) or the manufacturing sector as a whole (Column 2). Interesting results again occur when moving the analysis towards more disaggregated industry levels. As shown by the results presented in Column 3, the high-skill labor ratio increases statistically significant if offshoring takes place in the relative high-skill intensive industries. By contrast, in line with the results achieved with the RE regressions, if offshoring takes place in the relative low-skill intensive industries the effect on the industries skill ratio is not statistically significant. The results become again more detailed when considering which part of production is relocated abroad (Column 4). Both offshoring scenarios in the relative high-skill intensive X industry (if the X industry imports its low-skill intensive intermediates L or its high-skill intensive counterparts H) have a statistical significant positive effect on the industries high-skill labor ratio. The effect of both offshoring scenarios in the low-skill intensive industries is negative, statistically significant with the system GMM estimation considering offshoring of high-skill intensive production parts H.[17]

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[15] It is worthwhile to explain the increase in the sample-size to 330 observations and 40 groups when conducting the analysis at the more disaggregated level. The increase occurs by differentiating between two different parts of the production structure. In the last Column, we distinguish between relocating the low or high-skill intensive part of production. We thus end up with two different variables per industry what doubles the sample size.

[16] The table presents only the estimated coefficients of the variables of main interest. The complete results including all variables and overall model statistics are presented in Tables A3 and A4 in Appendix C.

[17] Since the GMM estimator was designed in the context of labor and industrial economics, where the number of observations is typically large, one might question the robustness of GMM-estimation results achieved with small samples as in our analysis, that are, however, typical for country studies. In this regard, Soto (2009) shows that GMM estimations are robust and efficient also in small-sample studies [42]. Moreover, the system GMM estimator proofs to have a lower bias and higher efficiency than all the other estimators analyzed. Regarding the GMM-estimations presented above, results of the robust Sargan/Hansen test show that the overidentifying restrictions are valid. Results of the Arellano-Bond test for autocorrelation show that there is no higher-order autocorrelation what indicates that our instruments are valid and

Table 4. Effects on the Industries' High-Skill Labor Ratio (Robustness Checks A).

	Whole Economy	**Manufacturing Sector**	**Disaggregated Industry Levels**	
	Robustness Check 1: 2SLS-Version			
VS	1.2420 (0.89)	1.1286 (0.81)	-	-
i VS (Y)	-	-	.6982 (0.50)	-
i VS (X)	-	-	2.4466 * (1.72)	-
i VS ($Y \to L$)	-	-	-	-0.0625 (-0.10)
i VS ($Y \to H$)	-	-	-	-1.3191 (-1.32)
i VS ($X \to L$)	-	-	-	5.3610 ** (2.21)
i VS ($X \to H$)	-	-	-	1.4968 * (1.72)
	Robustness Check 2: System GMM-Version			
VS	0.4611 (0.33)	0.5975 (0.70)	-	-
i VS (Y)	-	-	0.1181 (0.17)	-
i VS (X)	-	-	2.7045 * (1.85)	-
i VS ($Y \to L$)	-	-	-	-0.3316 (-0.78)
i VS ($Y \to H$)	-	-	-	-1.4622 ** (-1.94)
i VS ($X \to L$)	-	-	-	6.0819 ** (2.27)
i VS ($X \to H$)	-	-	-	1.8353 * (1.87)

Endogenous variable: within industries' high-skill labor ratio (H/L); (z-Statistics in parentheses); */**/*** indicates significance at 10/5/1 percent, all exogenous variables lagged by 1 period; System GMM instruments applied for H/L and standard IVstyle instruments for all other regressors.

exogenous. For the complete results of the system GMM estimations, also presenting the test statistics, see Table A4 in Appendix C.

Since it can be expected that industries need time to adjust their labor composition after offshoring occurred, interesting results may be achieved when increasing the time lag of the offshoring index VS. We performed additional regressions including the lagged VS-index by two periods as exogenous variables. Results completely support our main findings already presented above. It is interesting to note that the level of significance even increases slightly. The main results are presented in Table 5 Robustness Check 3.

Table 5. Effects on the Indistries' High-Skill Labor Ratio (Robustness Checks B).

	Whole Economy	**Manufacturing Sector**	**Disaggregated Industry Levels**	
	Robustness Check 3: 2-Lag-Version of the VS-Indices			
VS	2.0384 (0.60)	3.4553 (1.06)	-	-
i VS (Y)	-	-	−.4449 (−0.20)	-
i VS (X)	-	-	11.5353 ** (2.08)	-
i VS (Y → L)	-	-	-	−3.8587 * (−1.69)
i VS (Y → H)	-	-	-	−11.5782 *** (−2.55)
i VS (X → L)	-	-	-	29.1480 * (1.64)
i VS (X → H)	-	-	-	9.2336 ** (2.03)
	Robustness Check 4: Including Industry Specific Time Dummies			
VS	−4.3263 (−1.34)	−4.2973 (−1.36)	-	-
i VS (Y)	-	-	−3.5529 (−1.36)	-
i VS (X)	-	-	11.9154 (0.42)	-
i VS (Y → L)	-	-	-	−3.0196 * (−1.82)
i VS (Y → H)	-	-	-	−6.0630 ** (−2.29)
i VS (X → L)	-	-	-	14.2095 (1.47)
i VS (X → H)	-	-	-	4.0842 (1.06)

Endogenous variable: within industries' high-skill labor ratio (H/L); (z-Statistics in parantheses); */**/*** indicates significance at 10/5/1 percent.

As the results show, the VS-index also significantly affects the industries' high-skill labor ratio when lagging the index by two periods. Again, there are no significant effects when considering more aggregated industry levels, however, when moving towards a deeper disaggregation level, offshoring in the relative low-skill intensive Y industries is negatively correlated with the high-skill labor ratio (Column 3). The effect is statistically significant at the level of 10 percent if the respective low-skill intensive industry offshores its relative low-skill intensive production fragments (L). If the industry relocates its relative high-skill intensive fragments (H), the level of significance increases to the level of 1 percent (Column 4). By contrast, if offshoring takes place in the relative high-skill intensive industries (X), the effect of offshoring on the high-skill labor ratio is positive, even when the exogenous offshoring index is lagged by two periods (Column 3). Both positive effects, the one considering offshoring of the low-skill intensive production parts (L) as well as the one regarding offshoring of the high-skill intensive fragments (X) are at high levels of statistical significance (Column 4).[18]

Robustness Check 4 includes industry specific time dummies in order to allow for different developments over time across industries. This procedure can control for a possible technological progress. As already described above, our estimation strategy includes the variable traditionally used to proxy technological progress as endogenous variable: the factor composition of an industry. It is therefore not straight forward to decide whether or how to control for technological progress in our analysis. Robustness Check 4 therefore presents one possible solution. As the results show, effect of the VS-index on the industries high-skill labor ratio are less significant, however, keeping their tendency already shown with the other estimation strategies. The negative effect of offshoring in the low-skill intensive industries are still in the range of the usually reported significance-levels of 10 and 5 percent.

Robustness Check 5 discusses the significance and importance of the time dummies. Interpreting the year dummies in more detail shows that the estimation results for the high-skill labor ratio are not only driven by a positive time trend. If we run the regressions with a linear time trend instead of time dummies, the estimated coefficient of the time trend is positive (as one would assume when regarding Figure 2), but not significant. When including the control variables and our main exogenous variables (the offshoring index) and sticking to a possible linear time trend, our main results are the same as presented above and the estimated linear time trend is positive and statistical significant at the level of one percent. Relaxing the linearity assumption of the time trend and including time dummies instead (what yields the results presented above), the estimated time dummies are overall negative and statistically significant mostly at the level of 1 percent. This shows that it is important to fit the econometric model properly. The significance of the time structure and of the effects implied by the other macroeconomic variables (especially the VS-index) indicate that the increase in the high-skill labor ration can not be explained by the time dimension alone.

[18] Similar as in the robustness checks above, Table 5 presents only the main results. The complete results are presented in Table A5 in Appendix D.

5. Discussing the Results

As the empirical results for Germany show, implications on the high-skill labor ratio are mainly driven by the skill intensity of the industry where offshoring takes place, and only to a lesser extent by the skill intensity of the relocated production block. This supports the "sector bias" of offshoring. However, the empirical tendencies found here show opposite directions as expected from theory: whereas offshoring in relative high-skill intensive industries increases the high-skilled labor ratio (theory would predict a decrease), offshoring in relative low-skill intensive industries decreases the high-skilled labor ratio (theory would predict an increase). Even if our results seem to conflict with theory in this respect, they are in line with other empirical findings as e.g., the ones by Falzoni and Tajoli (2012) for the Italian economy [24]. Thus, there seems to be a puzzle regarding theoretical and empirical evidence.

Theoretical implications of offshoring on relative wages are mostly quite clear cut. While relative high-skill wages are expected to increase if offshoring takes place in relative high-skill intensive industries, they are expected to decrease if it takes place in relative low-skill intensive ones. The driving force behind these results is the assumption that offshoring induces a productivity-enhancing effect, similar than skill biased technological progress.[19] However, when turning to the effects on the high-skill labor ratio, as the industries' production structure, results are not as clear cut anymore. As mentioned in the theoretical section above, a wage-effect gets accompanied by an offshoring-effect, with the possibility of both effects outperforming each other. As shown in Horgos (2011b), the elasticity of substitution between low and high-skilled labor is one key parameter to solve this pattern [27]. If the elasticity of substitution is high enough, what is assumed in most of the theoretical models, the wage-effect outperforms the offshoring effect leading to the implications described in Hypothesis (iii) above: If offshoring takes place in the relatively high-skill intensive industry, industries shift production relatively towards more low-skilled labor as the relative wage of the high-skilled increases. Vice versa for the relative low-skill intensive industry. If, by contrast, the elasticity of substitution is below a critical level, there is the possibility that the offshoring-effect outperforms the wage-effect, with opposite results. In the specific context analyzed in this contribution, we know that the strength of the wage effect is limited by the low degree of wage flexibility in Germany. Thus, with respect to the empirical results found in the analysis above, it seems that substitutional forces as reactions on the wage effect are not as pronounced. Additionally, the extent and the composition of offshoring different production parts is of high importance for the resulting tendencies. There seems to be a significant force separating the industries. If the low-skill intensive industries conduct offshoring activities, their production gets more and more low-skill intensive, vice versa for the high-skill intensive industries.

A possible interpretation of these results is that in some industries there can be more complementarity than substitution between domestic production of parts and offshoring of some production phases (giving rise to a very low elasticity of substitution). For example, if a high-skill intensive industry offshores production of high-skilled parts, the workforce employed domestically must also be skilled to use those

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[19] For theoretical investigations see e.g., Arndt (1997, 1998a, 1998b) or Baldwin and Robert-Nicoud (2014) who recently generalized the HO model in order to consider trade in tasks [4–6,20]. Empirical evidence can be found e.g., in Horgos 2011 [13].

components, and therefore the high-skill to low-skill labor ratio does not decline with offshoring, but it might even increase moderately. A complementarity effect can also occur if offshoring allows the industry to expand: when expanding, low-skill intensive industries tend to increase the number of low-skill workers more than high-skilled workers, and vice versa in the high-skill intensive industries. This also can explain why offshoring always displays a negative effect on the H/L ratio in the low-skill intensive industries and a positive sign in the high-skill intensive industries.

Thus, whereas implications on relative wages are quite clear cut, implications on the industries skill ratio' are quite fuzzy, depending strongly on specific parameter assumptions and concrete empirical situations. Since it is not possible to capture all the theoretically assumed parameter values empirically it is of great interest to compare the findings of this contribution with those of other empirical examinations. As Falzoni and Tajoli (2012) show, results are similar for the Italian economy [24]. In addition, in Italy, the high-skill labor ratio increases if offshoring (measured with a narrow offshoring index) takes place in relative high-skill intensive industries and it decreases if offshoring takes place in relative low-skill intensive industries. Thus, it is interesting to have a closer look at the empirical offshoring situation in Italy compared to those in Germany. Despite several differences of these two economies concerning the structure and the composition of the manufacturing sector, it is interesting to note that offshoring is in both economies more pronounced in relative high-skill intensive industries compared to relative low-skill intensive ones. It is also worth remembering that in both economies, labor markets and especially wage rates are fairly rigid. Therefore, in both cases we can expect the wage effect to be weak, and to observe the offshoring effect prevailing.

Another finding that is one of the core results of both empirical analyses, and even supports the theoretical findings so far (summarized in Hypothesis ii), is that it is of great importance in which industry offshoring takes place. Supporting the sector bias, implications of offshoring on the industries' skill intensity differ strongly if offshoring takes place in the relative high or the relative low-skill intensive industries instead.

6. Conclusions

This contribution investigates the implications of offshoring on the industries' high-skill labor ratio. By contrast to the effects on relative wages, implications on the industries' production structure are not as clear cut. A more direct offshoring-effect gets accompanied by an indirect wage-effect, with the possibility of both effects outperforming each other. From a theoretical point of view results strongly depend on detailed assumptions, as e.g., the elasticity of substitution between high and low-skilled labor, and on the extent and composition of offshoring activities as well. Since there are only few contributions investigating the effects of offshoring on the industries' skill ratio, this paper tries to shed some more light into this discussion.

The value added of the paper is as follows: since the main part of offshoring literature focus on effects on relative wages, and since most empirical investigations are not based on clearly specified theoretical hypothesis, the paper summarizes the main theoretical findings on the effects of offshoring on the skill ratio in order to distill three testable hypotheses from the theory providing the base for the empirical analysis. The empirical analysis on the effects of offshoring on the industries' high-skill labor ratio presents the first results for the German economy, distinguishing clearly between the four possible offshoring scenarios (offshoring of low and high-skilled production fragments in either low or high-skill intensive industries). The effects on the skill ratio are mainly driven by the skill intensity of the industry where offshoring takes place and only to a minor extent by the skill intensity of the relocated production fragment. If offshoring occurs in the relative high-skill intensive industries, the industries' high-skill labor ratio increases, whereas it decreases if offshoring takes place in the relative low-skill intensive industries. This detailed result, however, seems to contradict with theory at first sight. Therefore, the paper further discusses the link between theoretical and empirical findings and the relation to other empirical examinations as well. From a theoretical point of view, results seem to crucially depend on the elasticity of substitution as well as on the extent and composition of the offshoring activity. In an empirical manner it is interesting to note, that in Germany and also in Italy (where a similar pattern could be achieved) offshoring is strongly pronounced in the high-skill intensive industries of the manufacturing sector and exhibits a complementarity effect on domestic production.

Our results offer several possibilities for future research. A comparative cross country analysis would be of high interest. What are the factors that seem to be stable across countries and what are the ones that seem to differ? Furthermore, it would be worth investigating the importance of measurement differences in this respect. Additional insights could be achieved from firm-level data. In order to concretely link theoretical findings to empirical examinations, the elasticity of substitution needs also to be taken into account empirically. This would be an additional area of great interest for future empirical investigations. It would also be of high interest to further examine in which situations offshoring exhibits a complementary or substitutional effect on the industries' production structure. This is especially relevant for a specific strand of current economic literature discussing if offshoring might harm high-skilled workers in industrialized economies as well.

Author Contributions

Both authors have contributed substantially to writing the manuscript, discussing the literature, describing the theoretical causalities and performing the empirical analysis.

Appendix A

In order to distinguish between high and low-skill intensive industries of the German manufacturing sector we refer to a cluster analysis done by Geishecker and Görg (2005) [10]. Using a k-means cluster analysis technique (with the use of a standard Euclidean distance measure) they group industries of the German manufacturing sector with respect to the education of the workers. This classification concept corresponds directly to the grouping intuition of our analysis. One could however also use other classification schemes as e.g., the OECD (2011) technology intensity definition [43]. Classification results of Geishecker and Görg (2005) are presented in Table A1 and compared with the OECD R&D intensities. As the table shows, the classification after skill intensities used in our analysis goes in hand with the OECD classification of R&D intensities.

Table A1. Classification of High-Skill and Low-Skill Industries.

Industry	NACE	OECD R&D Intensities
Low-Skill Intensive Industries:		
Food products and beverages/tobacco	15	low-tech. industry
Textiles	17	low-tech. industry
Wearing apparel	18	low-tech. industry
Tanning, dressing of leather	19	low-tech. industry
Wood products, except furniture	20	low-tech. industry
Pups, paper and paper products	21	low-tech. industry
Coke, refined petroleum	23	medium-low-tech. industry
Rubber and plastic products	25	medium-low-tech. industry
Other non metallic mineral products	26	medium-low-tech. industry
Fabricated metal products	28	medium-low-tech. industry
Furniture; manufacturing n.e.c.	36	low-tech. industry
High-Skill Intensive Industries:		
Publishing, printing and reproduction	22	low-tech. industry
Chemicals and chemical products	24	medium-high-tech. industry
Basic metals	27	medium-low-tech. industry
Machinery and equipment	29	medium-high-tech. industry
Office machinery and computer	30	high-tech. industry
Electrical machinery and apparatus	31	medium-high-tech. industry
Radio, television and communication	32	high-tech. industry
Medical, precision and optical instrum.	33	high-tech. industry
Motor vehicles, trailer	34	medium-high-tech. industry
Other transport equipment	35	medium-high-tech. industry

Source: Geishecker and Görg (2005) and OECD (2011).

Appendix B

Table A2 reports the results of the different tests applied to decide about the proper estimation strategy.

Appendix C

Table 4 in Section 4 only presents the main columns concerning the implications of the VS-index on the H/L ratio. The complete results for the 2SLS and the system GMM estimations are presented in Tables A3 and A4.

Table A2. Summary of Test Statistics.

	Whole Economy	**Manufacturing Industry**
Breusch and Pagan Lagrangian multiplier test for random effects		
chibar2(01)	292.88	282.23
Prob > chibar2	0.0000	0.0000
Hausman Test: Difference in RE and FE coefficients is not systematic		
chi2(3)	1.54	1.20
Prob > chi2	0.6738	0.0000
Modified Wald test for groupwise heteroskedasticity (H0: σ^2 for all i)		
chi2(25)	2.7e+31	2.2e+31
Prob > chi2	0.0000	0.0000
Wooldridge test for autocorrelation in panel data (H0: no first order AC)		
F(1,21)	4.115	17.564
Prob > F	0.0554	0.0005

Table A3. Effects on the Indistries' High-Skill Labor Ratio Robustness Check: 2SLS-Version.

	Whole Economy	**Manufacturing Sector**	**Disaggregated Industry Levels**	
H/L	0.9428 ***	0.9939 ***	0.9221 ***	0.9369 ***
	(9.77)	(9.66)	(7.82)	(12.23)
ω	−0.1887	−0.2689	−0.2333	−0.2167 **
	(−1.17)	(−1.51)	(−1.43)	(−2.03)
Q	3.05e-07	1.17e-07	−5.97e-07	−5.42e-07
	(0.52)	(0.18)	(−0.89)	(−1.11)
VS	1.2420	1.1286	-	-
	(0.89)	(0.81)		
i VS (Y)	-	-	.6982	-
			(0.50)	
i VS (X)	-	-	2.4466 *	-
			(1.72)	
i VS (Y → L)	-	-	-	−.0625
				(−0.10)
i VS (Y → H)	-	-	-	−1.3191
				(−1.32)
i VS (X → L)	-	-	-	5.3610 **
				(2.21)
i VS (X → H)	-	-	-	1.4968 *
				(1.72)
cons.	.5738 ***	.5580 *	.6044 **	.7179 ***
	(2.73)	(1.86)	(2.13)	(3.57)
Year Dummies	YES	YES	YES	YES
Obs.	185	163	163	326
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Endogenous variable: within industries' high-skill labor ratio (H/L); (z-Statistics in parantheses); */**/*** indicates significance at 10/5/1 percent, all exogenous variables lagged by 1 period.

Table A4. Effects on the Indistries' High-Skill Labor Ratio Robustness Check: GMM-Version.

	Whole Economy	**Manufacturing Sector**	**Disaggregated Industry Levels**	
H/L	0.8412 ***	0.9338 ***	0.8513 ***	0.8859 ***
	(8.37)	(16.45)	(12.56)	(16.33)
ω	−0.0558	−0.0986	−0.0903	−0.0808
	(−0.52)	(−0.82)	(−0.77)	(−0.98)
Q	1.19e-08	1.17e-07	−9.90e-07	-
	(0.02)	(0.17)	(−1.18)	
VS	0.4611	0.5975	-	-
	(0.33)	(0.70)		
i VS (Y)	-	-	.1181	-
			(0.17)	
i VS (X)	-	-	2.7045 *	-
			(1.85)	
i VS (Y $\rightarrow$ L)	-	-	-	−0.3316
				(−0.78)
i VS (Y $\rightarrow$ H)	-	-	-	−1.4622 **
				(−1.94)
i VS (X $\rightarrow$ L)	-	-	-	6.0819 **
				(2.27)
i VS (X $\rightarrow$ H)	-	-	-	1.8353 *
				(1.87)
cons.	−0.0827	−0.0239	0.0011 **	0.0152
	(−0.53)	(−0.18)	(0.01)	(0.22)
Year Dummies	YES	YES	YES	YES
Obs.	189	164	164	328
Groups	25	20	20	40
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Sargan/Hansen, Prob>chi2	1.0	1.0	1.0	0.41
Arellano-Bond:				
AR(1), Prob>chi2	0.126	0.13	0.13	0.03
AR(2), Prob>chi2	0.412	0.39	0.42	0.24

Endogenous variable: within industries' high-skill labor ratio (H/L); (z-Statistics in parantheses); */**/*** indicates significance at 10/5/1 percent, all exogenous variables lagged by 1 period; We applied GMM instruments for H/L and standard ivstyle instruments for all other regressors.

Appendix D

Since the effect of offshoring on the industries skill ratio may take its time, interesting results occur when including wider lags of the exogenous offshoring variable, the VS-index. We applied regressions using the 2-lag-version of the offshoring index. Complete regression results are presented in Table A5.

Table A5. Effects on the Indistries' High-Skill Labor Ratio Robustness Check: 2-Lag-Version of the VS-index.

	Whole Economy	**Manufacturing Sector**	**Disaggregated Industry Levels**	
ω	-0.0520 (-0.76)	-0.0784 (-1.10)	-0.0750 (-0.97)	-0.0573 (-1.21)
Q	$7.56e$-07 (0.34)	$1.62e$-06 (0.62)	$-3.39e$-06 (-1.02)	$-2.83e$-06 (-1.15)
VS	2.0384 (0.60)	3.4553 (1.06)	-	-
i VS (Y)	-	-	-0.4449 (-0.20)	-
i VS (X)	-	-	11.5353 ** (2.08)	-
i VS (Y $\rightarrow$ L)	-	-	-	-3.8587 * (-1.69)
i VS (Y $\rightarrow$ H)	-	-	-	-11.5782 *** (-2.55)
i VS (X $\rightarrow$ L)	-	-	-	29.1480 * (1.64)
i VS (X $\rightarrow$ H)	-	-	-	9.2336 ** (2.03)
cons.	1.6649 *** (5.11)	1.4107 *** (3.04)	1.5373 *** (4.32)	1.9776 *** (5.68)
Year Dummies	YES	YES	YES	YES
Obs.	168	147	147	294
Groups	25	20	20	40
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Endogenous variable: within industries' high-skill labor ratio (H/L); (z-Statistics in parantheses); */**/*** indicates significance at 10/5/1 percent, all exogenous variables lagged by 1 period, the VS-index lagged by 2 periods.

Conflicts of Interest

The authors declare no conflict of interest.

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